Genetic Algorithm Optimization of Operating Parameters for Multiobjective Multipass End Milling

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Abstract— **Genetic Algorithm are capable of handling a large number of design parameters and work for optimization problems that have discontinues or non-differentiable multidimensional solution spaces, making them ideal for optimization of machining parameters. Current paper is based on Genetic Algorithm (GA) for optimization of process parameters (e.g. feed and speed) for multi-objective multi pass end milling. GA has been implemented using the MATLAB environment on the objective function, which is a hybrid function of cost and time, feed and speed. The results of optimum cost, feed and speed have been calculated after GA based implementation with PSO based implementation and conventional results. The GA results are found better in terms of the objective function as compared with PSO results for the multi-objective multipass end milling process.**

Index terms: **Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Crossover, Mutation, chromosome**

I. INTRODUCTION

The selection of tools, fluid, operating conditions etc. is based upon a rational optimization procedure, where very strong economic or production rate constraints pertain, in material removal process in workshop. While the most important optimization variable is usually total cost per part, there are occasions when maximum rate of production and time for production are also considered important. The cost to produce one work piece is made up of money spent for machine operations, overheads, time spent for loading, for rapid advance, feed, rapid return and for unloading. So it is important to optimize the production time along with production cost by selecting optimum feed and speed in the end milling process.

II. LITERATURE REVIEW

Though a lot of research in milling machining and optimization has been attempted by various researchers, few selected papers relevant in this study and the issues related to milling machining and optimization have been discussed in this section. **Tondon et al. [1]** used particle swarm optimization for optimizing multiple machining parameters and results in 35% reduction in machining time. **Conceição et al. [3]** optimized the multi-pass cutting parameter in face milling using genetic search. **Saffari et al. [4]** used Genetic Algorithm for Optimization of the Machining Parameters to Minimize

Tool Deflection in the End Milling Operation. **Patwari et al. [5]** described mathematically the effect of cutting parameters on surface roughness in end milling of Medium Carbon Steel. The mathematical model for the surface roughness has been developed & solved in terms of cutting speed, feed rate, and axial depth of cut. **Gupta et al. [6]** proposed a Hybrid Genetic Algorithm (HGA) to optimize the non-productive tool path in which the initial seed solution is generated by special heuristic and combined with random initial solution generated by simple genetic algorithm (SGA). **Basker et al. [7]** used GA, Tabu search, Ant colony Algorithm and Particle swarm optimization algorithm for optimizing milling machining parameters. **Wang et al. [8]** used Genetic simulated annealing for determining optimal machining parameter for multi-pass milling **Reddy et al. [9]** developed mathematical models based on Response Surface Methodology to determine the effect of tool geometry and cutting conditions for machining performance and also optimize the surface roughness with Genetic Algorithm. **Savas et al. [10]** used GA for optimization of surface roughness and results in minimum surface roughness and increase in surface roughness with increase in depth of cut and feed rate. **Abburi et al. [11]** used RGA (real-parameters Genetic Algorithm) for optimization of multi-pass turning process, results in minimizing product time which is the base for SQP (Sequential Quadratic Programming) code and results in further improvement. **Mukherjee et al. [12]** reviewed the optimization techniques for metal cutting processes and proposed a systematic approach to determine optimal or near-optimal cutting conditions in various kinds of metal cutting process optimization problems. **Onwubolu [13]** proposed a new optimization technique based on Tribes for determination of the cutting parameters in multi-pass milling operations such as plain milling and face milling. **Chengqiang et al. [14]** proposed the combination of orthogonal experimental method and genetic algorithm method for the optimization of milling parameters, in order to improve the tool life to ensure the processing efficiency.

III. METHODOLOGY

The algorithm for the current methodology is designed according to following two steps. The first step involves the validation of Genetic Algorithm with Particle Swarm Optimization for multi-objective single-pass end milling and the second step is the implementation of Genetic Algorithm

for the multi-objective multi-pass end milling optimization using the same objective function as used in single pass optimization problem. The multi-pass optimization of the objective function will be further done in two phases:

Phase-I: First phase consists of Volume Sectioning Method for the developing the database for the depth of the cut(s) and determining tentative number of passes for achieving total depth of cut. The volume sectioning can be considered as a multi-stage decision process in which each of the single-stage optimization problems can be stated such that the volume to be cut is divided into possible sections called as depth of cut(s). The selection of a proper number of sections for the problem has extreme importance as higher precision i.e. selecting the higher number will increase the execution time, although more effective optimal values may have been calculated for the objective function.

Phase-II: The second phase involves the GA optimization of the objective function along with its speed, feed and depth of cut. The optimization of cost function, speed and feed will be supported by finding the tool life and surface roughness for single-pass and multi-pass end milling.

The objective function proposed in literature for multi-objective multi-pass end milling is discussed as follows:

A. The machining time (Ref.[1])

$$t_m = \frac{\pi . L . D.}{1000. v . Z . S_z} \left(\frac{W}{b}\right) \qquad .. (1)$$

Where is length of work piece (mm), D = cutter diameter (mm), W = width of work piece (mm), v = cutting speed [m/min], Z = number of teeth / flutes, S_z = feet per tooth [mm/tooth] and b = width of cut / radial depth of cut [mm].

B. Tool life (for i^{th} operation) (Ref.[1])

$$T_i = \frac{C_v^\alpha D^w}{V_i^\alpha S_z^\beta d_i^\gamma b_i \gamma Z^\lambda} \qquad .. (2)$$

Where d=axial depth of the cut [mm], $\alpha, \beta, \gamma, \omega$ and λ are the exponents in the tool life equation and are experimentally determined. Also C_v is the constant of proportionality. Note that these variables are unique for different tool-work-piece combination.

C. Surface Roughness (for i^{th} operation) (Ref.[1])

$$R_i = 318 * f^2 / 4d \qquad .. (3)$$

R_i = surface roughness (microns), f=feed rate (mm/min) and d=cutter diameter (mm)

D. Production cost, C, for milling [1] (from (1) & (2))

$$C = A_1 + A_2 . v^{-1} . S_z^{-1} . b^{-1} + A_3 . v^{\alpha-1} . S_z^{\beta-1} . d^\gamma . b^{-1} \qquad (4)$$

For the cost function C [4], can be written as

$$C = \frac{F}{x_1} + G * x_1 * x_2 \qquad (5)$$

Where

$$A_1 = M.t_1 \quad A_2 = \frac{\pi . L . D . M . W.}{1000. Z} \quad A_3 = [M.t_c + C_t] \frac{\pi . L D W Z^\lambda}{Z . C_v^\alpha . D^\omega}$$

$$F = 5 * 10^{-5}, G = 8.186 * 10^{-20},$$

$$x_1 = Feed\ rate\ (f) = \frac{1000\ Z\ v\ S_z}{\pi D},$$

$$x_2 = Spindle\ rate\ (N) = \frac{1000\ v}{\pi D}$$

$$Cost = Finish\ cost + (passes * cost\ for\ single\ pass) \quad .. (6)$$

To establish repeatability and robustness of the algorithm, V. Tondon et al. [1, 2] used the following machining conditions for HSS end milling cutter on machine tool TRIAC 3-axis CNC milling machine by Denford [1]: radial depth of the cut = 0.75 D, axial depth of cut = 0.25 in, cutting diameter = 0.25 in, number of flutes = 2, rake angle = 14°, primary clearance angle = 16°. The results are compared with V. Tondon [1] taking same set of constraints. Thus the problem consists of minimizing the cost function under given constraints.

IV. GENETIC AALGORITM IMPLEMENTATION

Genetic Algorithm is modeled after the processes of evolution and genetic recombination. The building blocks of the algorithms are named after genetic elements. Genetic Algorithm are inspired by Darwin's theory of the survival of the fittest, which states that in nature, competition among individuals for scant resources such as food and space results in the fittest individuals dominating over weaker ones. Only the fittest individual will survive and reproduce, while the weaker individuals die out. Genes are the binary encoding of each problem variable, and of the genes as a string are referred to as a chromosome. A set of chromosomes is called a population. Each chromosome in a population has a fitness associated with it, which is calculated through a fitness function. The chromosomes in each population are ranked from best to worst based on their fitness. The higher ranked chromosomes are mated to produce a new population that exhibits characteristics of the better individuals from the previous generation. Mutation is allowed to occur at a small probability. This process repeats until either a desired fitness has been achieved or a set number of generations have occurred.

The building blocks of GA are the schema. A Schema is a similarity template describing a subset of strings with similarities at certain positions. A schema represents a subset of all possible strings that have the same bits at certain string position i.e. a schema is a set of bit strings that can be described by a template made up of one (1s), zeros(0s) and asterisks(*s). The alphabet {0,1,*} can be used to represent any pattern of binary strings as one wishes. Each string represented by a Schema is called an instance of the Schema because the symbol * signifies that a 0 or a 1 could occur at the corresponding string position, the schema ***** represents all the possible strings of the five bits. The fixed positions of the schema are the string positions that have a 0 or a 1: in *000, a third, the forth and the fifth positions. In a given population, this is determined by the average fitness of instances of the schema.

Schemata with high fitness values, small defining lengths and low order are called building blocks. Short, low order and

highly fit schemata are sampled, recombined and resample to form strings of potentially higher fitness. By working with these particular schemata, the complexity of the problem is reduced. The genetic operators- crossover and mutation- generate, promote and juxtapose building blocks to form optimal strings. Crossover tends to conserve the genetic information present in the strings to be crossed. Thus, when the strings to be crossed are similar, its capacity to generate new building blocks diminishes. Mutation is not a conservative operator and can generate radically new building blocks. Selection provides the favorable bias towards building blocks with higher fitness values and ensures that they increase in representation from generation to generation. The building block hypothesis assumes that the position of good building blocks yields good strings. The GA implementation procedure steps are described below.

1. Generate population of a n chromosomes

2. Evaluate the fitness of each chromosome in the population. Find the sequence incurring minimum processing time.

3. Update new population by repeating the following

a. Select two parent chromosomes from the population for crossover with crossover probability to form new offspring sequences.

b. Select one parent chromosomes from the population for mutation with mutation probability to form new offspring sequence.

c. Replace old offspring with new off springs.

4. if the end condition is satisfied, then stop and return the best solution otherwise repeat the procedure and goto step 2. Use new generated population for a further run of the algorithm.

In present methodology, a thirty-two bit chromosome is selected for representing two variables of sixteen bit each, which are speed and feed respectively (parents). The decimal value of the variables are input, randomized and converted into binary variable for crossover and mutation. After performing crossover and mutation, the variables are again converted into decimal to get the parameters. The objective function provides the mechanism for evaluating the fitness each chromosome. In end milling, the objective (eqn-3) is to optimize the cost function and corresponding parameters (e.g. speed and feed) for given conditions of machine power, material, cost etc. While GA implementation, two parent chromosomes from population are selected for crossover and one parent chromosome is selected for mutation to generate the child sequences which will replace the parent sequences based on phenomenon of natural selection. The two site crossover and swap mutation methodology in GA is described in fig 1(a&b).
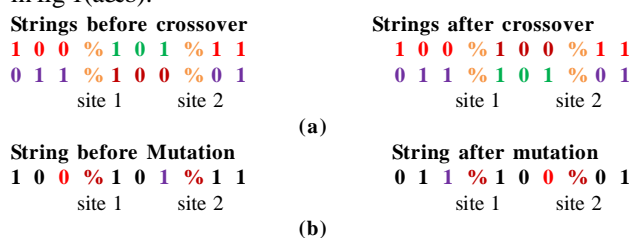
Strings before crossover
```
1 0 0 % 1 0 1 % 1 1
0 1 1 % 1 0 0 % 0 1
    site 1      site 2
```

Strings after crossover
```
1 0 0 % 1 0 0 % 1 1
0 1 1 % 1 0 1 % 0 1
    site 1      site 2
```

(a)

String before Mutation
```
1 0 0 % 1 0 1 % 1 1
    site 1      site 2
```

String after mutation
```
0 1 1 % 1 0 0 % 0 1
    site 1      site 2
```

(b)

Fig 1: (a) Two point Crossover (b) Swap Mutation

V. RESULTS AND DISCUSSIONS

Genetic Algorithm is developed and implemented for multi-objective multi-pass end milling process to calculate the process parameters using MATLAB software. The aim was to optimize the feed rate and spindle speed for obtaining optimum cost function for multi-objective multi-pass end milling process. The program is run with 50 generations with a population size of 30. The GA program is run on Intel Pentium Core I3 Processor with 4 GB RAM. Table 1 shows the results of PSO (Ref. [1]) implementation on the designed problem (objective function). Using PSO implementation, the minimum cost is 4.086 $/piece compiled with 12th generation at run no. 5.

TABLE 1: PSO RESULTS (MULTI-PASS END MILLING) (REF. [1])

GA Results For Multi Pass End Milling				
Run No	Generation	Cost $/piece	Feed mm/min	Speed rpm
1	3	4.0984	122	1495
2	25	3.9683	126	1461
3	48	3.9683	126	1445
4	11	3.9683	126	1497
5	3	3.9683	126	1497
6	26	3.9683	126	1497
7	50	3.7313	134	1469
8	22	3.9683	126	1481

Table 2 shows the results of GA implementation on the designed problem on which PSO was implemented using same set of variables, constraints and boundary conditions. The minimum cost calculated using GA implementation is 3.7313$/piece compiled at 50th generation for program run no. 7 as compared to PSO results which was 4.086$/piece.

TABLE 2: GA RESULTS (MULTI-PASS END MILLING)

PSO Results for Multi-pass End Milling				
Run No	Generation	Cost $/piece	Feed mm/min	Speed Rpm
1	12	4.094	122.27	1498
2	15	4.100	121.93	1495
3	18	4.099	121.95	1498
4	26	4.135	120.9	1497
5	12	4.086	122.39	1500
6	21	4.097	122.03	1498
7	6	4.088	122.29	1499
8	11	4.097	122.03	1498

Figure 2 shows the comparison of the cost function calculated after Genetic Algorithm and Particle Swarm optimization implementation (Ref. table 1 and table 2). The optimum cost for the designed problem as calculated by GA implementation is 3.7313$/piece at feed rate 134mm/min and speed 1469 rpm for the 7th run of the program whereas the optimum cost for the PSO implementation is 4.086$/piece at feed rate 122.39mm/min and speed 11500 rpm for the 5th run (Ref. [1])

After validating the Genetic Algorithm methodology for multi-objective single-pass end milling, tool life in multi-pass and single-pass end milling was computed and compared. Figure 3 shows the comparison of tool life for multi-objective multi-pass and single-pass end milling. The results show that there was increase in tool life by 7.36% in multi-pass end milling than single-pass end milling for same depth of cut
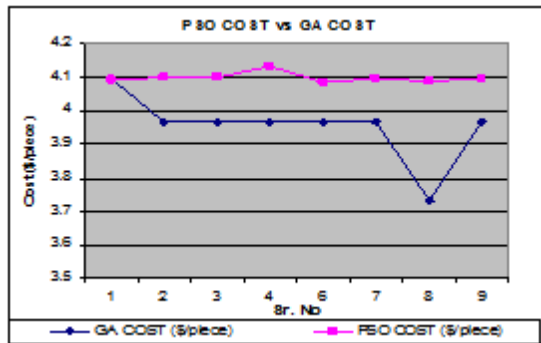
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Fig2: PSO and GA Cost Comparison

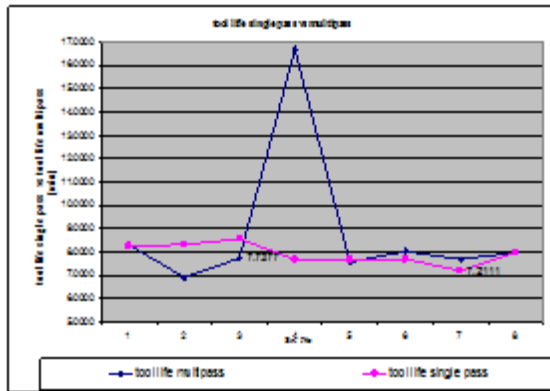(6.4mm) using two rough passes of 2.5mm and one finish pass of 1.4mm.

Fig 3: Tool life of multipass and single pass end milling

Genetic Algorithm methodology was applied for calculating the surface roughness on multi-objective multi-pass & single-pass end milling for same depth of cut (6.4mm as above). The surface roughness in multi-pass and single-pass end milling were computed and compared.
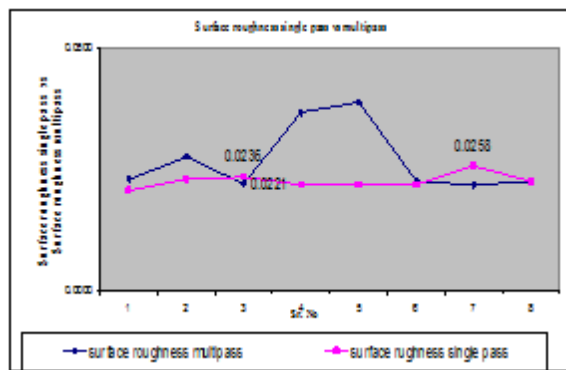

Fig 4: Surface Roughness after multipass and single pass end milling

Figure 4 shows the comparison of tool life for multi-pass and single-pass end milling. The results show that there was decrease in surface roughness by 8.5% and hence it can also be said that the surface become more smooth after multipass milling.

VI. CONCLUSIONS

In the present study, the cost function, a function of machining cost and time, is optimized by optimizing the two input parameters e.g. feed rate and spindle speed for using

MATLAB software. There are a number of constraint, few of them are assumed as constants (depth of cut, force, pressure, fatigue, angular pitch etc.) and few are kept variable to find their values at which the cost function is optimum (e.g. feed, speed etc.). Optimization techniques namely Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are implemented for calculating the cost and associated speed and feed for multi-objective single-pass end milling. The GA proved to be better for calculation of cost function for same set of variables and constraints. The Genetic Algorithm is then implemented for multi-objective multi-pass end milling for calculation of cost function, tool life and surface roughness and the results were compared with those of multi-objective single-pass end milling. This results in substantial increase in tool life and surface finish due to reduction in surface roughness for multi-pass end milling. So it can be concluded that same objective function along with same set of variables constraints and boundary conditions have been used for both of the methodologies used in the present paper i.e. GA and PSO. The GA implementation multi-objective multi-pass end milling gives better set of feed rate and spindle speed as compared to PSO implemented for multi-objective multi-pass end milling due to lesser value of cost function calculation. GA is better due to the fact that PSO covers lesser range of population and can be struck into local maximum, while GA gives optimum results in lesser number of iterations as it covers entire range of population and is more iterative.

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